Multi-Tier and Pool Residual Convolutional Neural Network Architecture for Glaucoma Grade Classification

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Abstract

Technology development has its major footsteps in medical applications. One of the major health care applications is glaucoma detection. There are several researches based on cup and disc segmentation of retinal images. As neural networks has its development in research field, several researchers focus on Convolutional Neural Network (CNN) for their research. In this research, a novel Multi-Tier and Pool Residual CNN (MTPRCNN) is designed for glaucoma detection. Due to reduction in computational cost, training time of network and overfitting, pool residual CNN is used. On account of better feature extraction and improved network training, multitier CNN is implemented as a combination with pool residual CNN. It consists of three tiers with three convolutional layers. This research uses MIAG RIM-one r1 dataset for its experiments. The dataset is divided into five different grades. The experimental results obtained 96.7% accuracy with 90.9% sensitivity. It is also tested with Random Forest (RF) Classifier which gives 97.5% accuracy with 93.6% sensitivity.

Keywords: glaucoma, retinal images, convolutional neural network

I. Introduction

‘Glaucoma’ is a Greek word, which means ‘clouded or blue-green hue’. A person who has a dilated cornea or is developing a cataract may be impacted by the ongoing increase in intraocular pressure inside the eye. A disease called glaucoma causes damage to the optic nerve, which leads to permanent visual loss [1]. The main cause of this is the constant strain on the eyes. Aqueous humor, also known as vitreous fluid, is secreted by the ciliary body into the posterior chamber between the iris and the lens, where it then drains through the trabecular mesh network.

For normal eyes, the secretion of fluid is balanced by the drainage [2]. But for glaucomatous eyes, the drainage canal is absolutely blocked which leads to the growth in strain, known as intraocular pressure which damages the optic nerve. If this damage is not treated earlier, it will lead to blindness. Glaucoma is the primary cause of blindness worldwide. Glaucoma affects one in two hundred of the people aged fifty and younger and one in ten over the age of eighty. As mentioned earlier, it cannot be identified at its early stages. Regular eye checkups by qualified professionals are important [3].

Fig. 1.1 depicts the different stages of glaucoma as it grows. Early glaucoma detection allows for less therapy and a reduction in damage and vision loss. Before the onset of glaucoma, the Optical Nerve Head (ONH) and Retinal Nerve Fiber Layer (RNFL) would initially undergo some structural alterations. Yet, assessments of these changes are subjective and have a significant level of inter- and intra-observer heterogeneity. Assessment of optic disc morphology is now more objective and quantitative because to the development of modern optical imaging techniques [4].

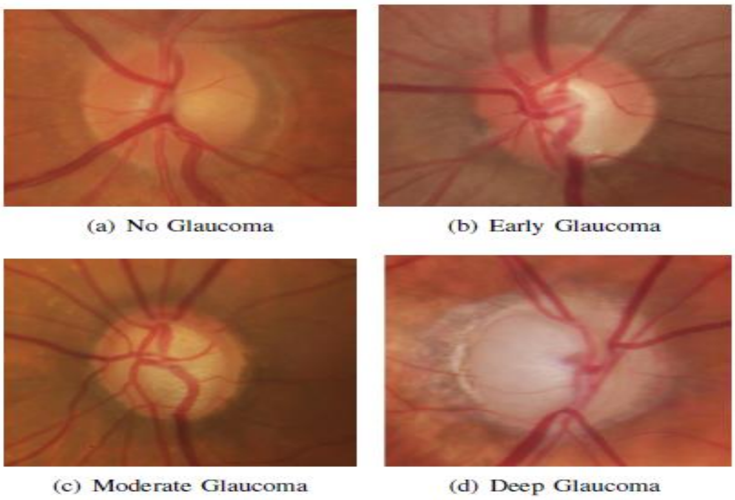

Fig. 1 Retinal Fundus Images of the ONH – Normal and Pathological eyes [5]

A big Optic Disc (OD) size has been proposed as a risk factor for the retinal disease glaucoma in recent studies. Since the optic nerve fibers converge in a circular area called the ONH, as glaucoma worsens, it destroys the nerve fibers and alters the curvature of the ONH [6]. The heterogeneity in the ONH's appearance brought on by imaging contrast and blood vessel obscurity frequently justifies a subjective manual screening and analysis.

The quantity of ganglion cells and the visual sensitivity for glaucoma detection are correlated. Several criteria have been proposed for the diagnosis of glaucoma, including the size of the cup, the narrowness of the surviving disc rim, the vertical ovality of the cup, and gradual changes in the cup. Locating further impacted areas will be easier if the position, center, and radius of the OD can be determined with more accuracy. Patients who have just minor visual impairment or diminished color clarity can also be identified.

Several health care applications including Glaucoma detection are discussed in [7]. In this paper, a novel multi-tier and pooling residual CNN based deep learning architecture has been designed with Empirical Wavelet Transform (EWT) decomposition. This method improves the efficiency of single scale CNN. The proposed method classifies the RIM-One r1 dataset into five different grades.

The remaining of the paper is organized as follows: Section II gives some related works on glaucoma detection that used deep learning architecture. Section III elaborates the proposed methodology with all the steps and design of deep learning architecture. Section IV demonstrates the proposed network with some experimental results. Section V concludes the work.

II. Related Works

For OD segmentation and glaucoma detection, the GD-YNet framework for unique context-aware deep learning has been created [8]. It takes advantage of the flexibility of YNet architecture and the possibility of aggregated modifications for context-aware OD segmentation and binary classification for glaucoma detection. Tripartite Tier Convolutional Neural Network Scheme (TT_CNN Scheme) has been developed to diagnose glaucoma [9].

In [10], Local Region Recursive Segmentation (LRRS) is used to separate the optic disc region from the input retinal image. Using this technique, the discriminative features are retrieved from the segmented optic disc. This technique uses the Local Vector Pattern (LVP) to consider the pairwise vector directions of the referenced pixel and its surrounding area in order to recover the micro level details of the optic disc. After extraction, the final image is divided into smaller, more detailed sub-images using a 2D Little Wood Paley (LWP) EWT. Z-score normalization is used to decompose the sub-images and normalize their features. Different classifiers are used to classify the final features.

For the automated identification of glaucoma from fundus images, the Evolutionary Convolutional Network (ECNet) is an innovative non-manual feature extraction technique [11]. Convolutional, compression, Rectified Linear Unit (ReLU) and summation layers are among the layers that are included, and these levels make it easier to extract discriminative features. The weights at various layers are optimized using a genetic method known as Real-Coded Genetic Algorithm (RCGA). The criteria used to train the ECNet maximizes the distance between classes and reduces the variance within classes.

The difficulties associated with implementing deep adversarial learning are shown in [12]. Many of the difficulties and challenges that researchers would face while implementing this form of technology are described and examined in this paper. Compact Self-Organized Operational Neural Networks (Self-ONNs) are developed in [13] and their performance is compared to that of traditional CNNs for the early detection of glaucoma in fundus images.

In [14], a new framework for deep convolution neural network-based glaucoma detection was developed. This system uses the Contrast Limited Adaptive Histogram Equalization (CLAHE) as a pre-processing step to improve local contrast. Additionally, they used two segmentation models (EfficientNet+U-Net) to separate the optic cup and disc mask from pictures of the retinal fundus. Additionally, the segmented optic cup and disc masks are used to calculate the Cup to Disk Ratio (CDR). Based on the CDR ratio, it determines if the input image has glaucoma or not.

A perceptron-based convolutional multi-layer neural network has been used to conduct glaucoma classification [15]. Entropy-based estimation is used to identify the border between the optic disc and optic cup. Following the segmentation of the optic disc and cup boundary, weighted least square feet is used to obtain the disc ratio and holistic local features. To accurately classify glaucoma in retinal pictures, it is tested on several datasets, including the Drishti-GS and Rim-ONE datasets.

Deep CNN has been used to create the Automatic feature Learning for Glaucoma Detection based on Deep LearnINg (ALADDIN) [16]. The creation of a deep learning architecture using CNN has been created for automated glaucoma diagnosis [17]. For diagnostic purposes, deep learning systems, like CNNs, can infer a hierarchical representation of images by differentiating between glaucoma and non-glaucoma patterns.

Al-Bander et al. have investigated the possibility of developing an automatic feature learning system for detecting glaucoma in colored retinal fundus images [18]. A fully automated method based on CNN is developed to distinguish between normal and glaucomatous patterns in order to make diagnostic conclusions. In contrast to conventional approaches, where the optic disc characteristics are manually produced, CNN automatically extracts the features from the raw images and feeds them to the Support Vector Machine (SVM) classifier to classify the images into normal or abnormal.

Using fundus images, a generalized deep learning model for glaucoma detection has been created [19]. The model is trained and tested on various datasets and architectures, in contrast to earlier studies. A novel approach based on Bit-Plane Slicing (BPS), Local Binary Pattern (LBP), and Gray-Level Co-occurrence Matrix (GLCM) is used [20]. First, fundus images are separated into channels like red, green and blue, and these separated channels are split into plans using BPS. Then, LBP images are obtained from selected green channel images. Second, we extract features based on GLCM from LBP images. Finally, using a least-squares SVM classifier, the higher ranked features are employed to classify glaucoma stages.

In [21], a system is created to classify glaucoma through fundus images using the CNN with Residual Network-34. A total of 2156 fundus images were used in the work. The data is divided into five types of glaucoma: early, moderate, deep, OHT, and normal.

Another system is designed using CNN with MobileNet architecture [22]. It has two convolution parts: depth-wise convolution and poin-twise convolution. The function of the Depthwise Convolution is to apply a single convolution filter per input channel, while the function of the point-wise convolution is to build new features by calculating the linear combination of the input channels by applying the 1x1 convolution.

A Computer-Aided Diagnosis (CAD) method for the classification of glaucoma stages using Image Empirical Mode decomposition (IEMD) has been designed in [23]. In this study, IEMD is applied to decompose the pre-processed fundus photographs into different Intrinsic Mode Functions (IMFs) to capture the pixel variations. Then, the significant texture-based descriptors have been computed from the IMFs. A dimensionality reduction approach called Principal Component Analysis (PCA) has been employed to pick the robust descriptors from the retrieved feature set. They have used the Analysis of Variance (ANOVA) test for feature ranking. Finally, the LS-SVM classifier has been employed to classify glaucoma stages.

III. Proposed Methodology

In this research, a novel deep learning architecture is designed with CNN using three tiers and pooling residual. The proposed system architecture is shown in Fig. 2. The input images are pre-processed with resizing and filtering (median filter). The input RGB image is converted into grayscale. The original image is resized to 64 x 64 which is then given to EWT decomposition which is discussed in the following subsection. The EWT coefficients are given to the designed CNN model. The CNN model extracts the features and classifies the images into five different grades.

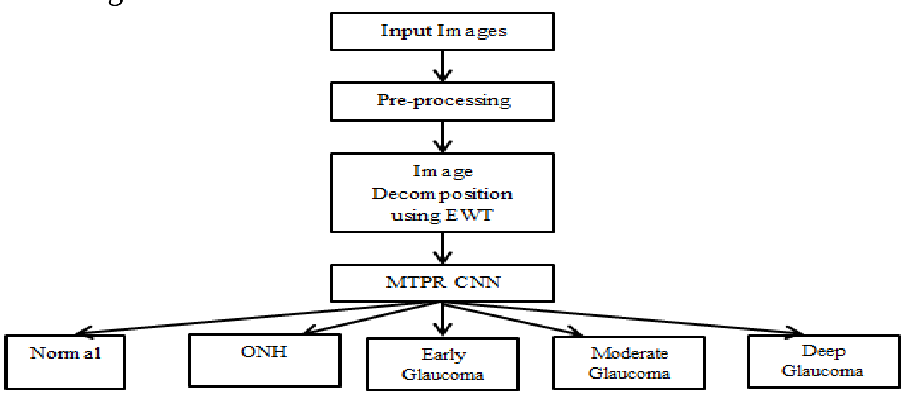

Fig. 2 System Architecture of the Proposed MTPRCNN Method

EWT Decomposition

A wavelet filter bank is created using the EWT decomposition technique, which divides a signal's high and low frequency components using channels. It is a signal-dependent method that does not make use of predetermined basis functions and decays a picture on wavelet tight edges that are generated adaptively. The method entails identifying the Fourier range backings of specific modes and using those backings to define a two-dimensional empirical type of Littlewood-Paley type wavelets [24]. The row and column of the input image are processed using classic wavelets using 1D EWT.

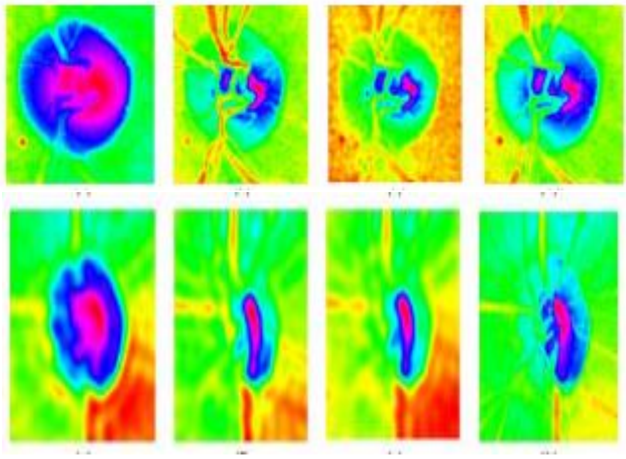

Fig. 3 EWT Decomposed Images

Proposed Multi-Tier Pooling Residual CNN architecture:

We designed a multi-tier pooling residual CNN with three tiers. The proposed CNN consists of convolutional layers, pooling layers, addition layers, concatenation layers, Fully Connected (FC) layers and softmax layer. We have used maximum pooling and average pooling wherever necessary. In the first convolutional layer, the layers divided into three tiers: top, middle and bottom.

The designed multi-scale CNN starts with the input layer. The EWT decomposed images are given to input layer which is then followed by 3 convolution layers (Conv1, Conv2, Conv3) of three tiers. The output from these convolution layers are again given to 3 convolutional layers (Conv4, Conv5, Conv6) in each tier. These convolutions are followed by pooling layers (AvgPool1, MaxPool1, MaxPool2). For top and middle tiers, maximum pooling is used, whereas the bottom tier uses average pooling.

The pooled features are again convolved by 2 level convolutions (Conv7 to Conv12). The pooled and convolved features are added in addition layer (Addition1, Addition2, Addition3). The added features are again pooled in each tier (MaxPool3, AvgPool2, MaxPool4). This process is repeated once from the previous pooling. In the final pooling, dropout layer is added which is then given to FC layers (FC1, FC2, FC3). The three FC layers are concatenated using concatenation layer. Finally, FC is used to obtain class level outputs. The predicted class is given by softmax layer.

In the top tier, the kernels for convolution are set to 7 x 7 with 64 filters. In the middle tier, the kernels are set to 3 x 3 with 64 filters. In the bottom tier, the kernels are set to 5 x 5 with 64 filters. In all the tiers, the pooling layers are set to 5 x 5. Figure 4 displays the layer details in each tier

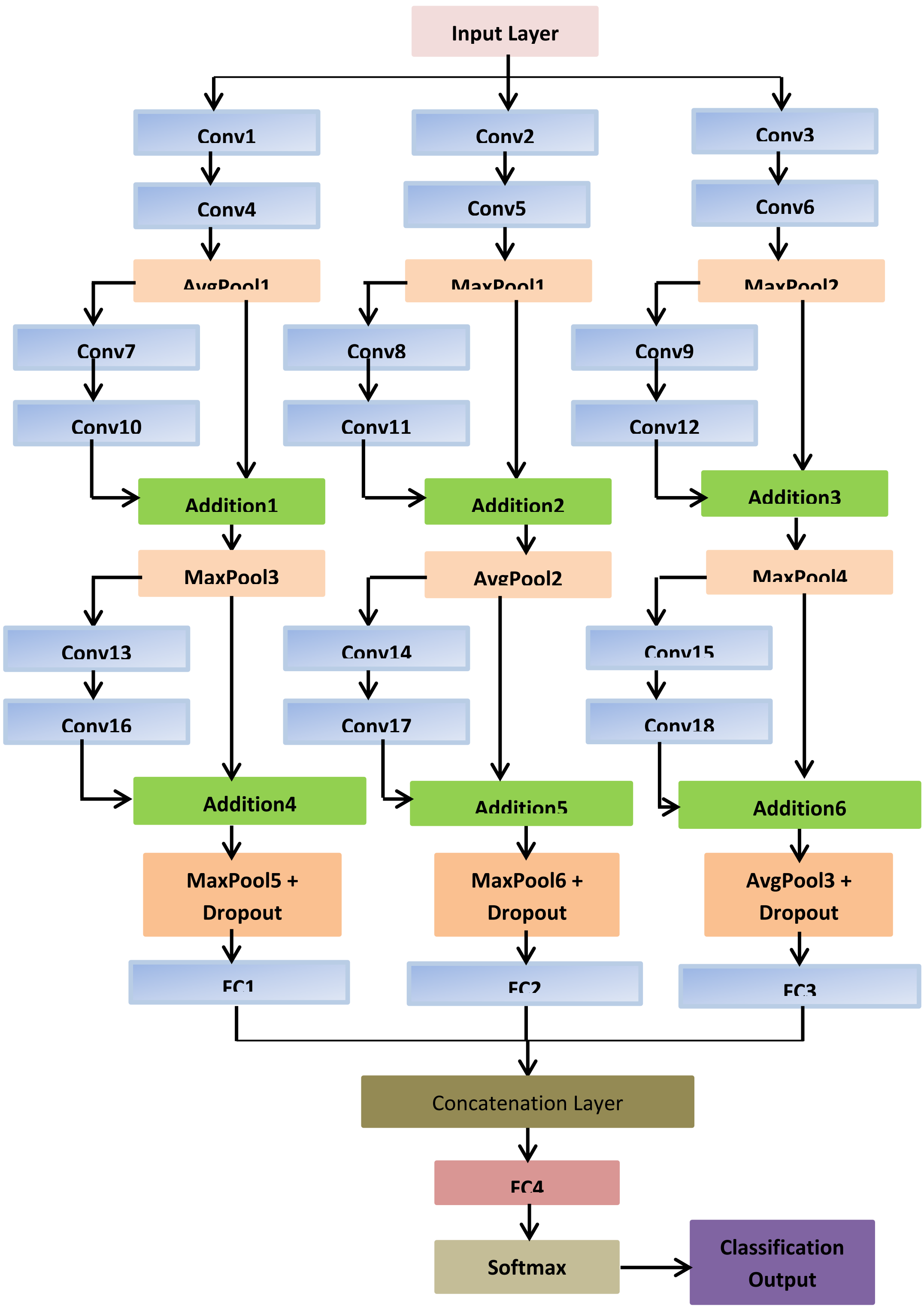

Fig. 4 Detailed Layer of MTPRCNN Architecture

Table 1 shows the detailed parameters that are set in each layer. Table 2 displays the architecture of the three tiers alone. The input layer is excluded in the table as it contains only the input size as the parameter.

Table 1 Layer Details of MRPRCNN

Tier	Layer	# filters , size	Input Size
Top Tier	**Convolution layers**	64, 7 x 7	224 x 224 x 64
	FC3		1 x 1 x 100
Middle Tier	**Convolution layers**	64, 3 x 3	224 x 224 x 64
	FC2		1 x 1 x 100
Bottom Tier	**Convolution layers**	64, 5 x 5	224 x 224 x 64
	FC1		1 x 1 x 100
All Tiers	**Pooling Layers**	5 x 5	224 x 224 x 64
Concatenation Layer		-	1 x 3 x 100
FC4		-	1 x 1 x 5
Softmax		-	1 x 1 x 5

We have dropout layers after the last pooling layers with a ratio of 0.5. In all the convolution and pooling layers, stride is set to 1 x 1 and padding is set to 0. Hence there is no change in feature size in each layer. Finally the output is differentiated as five classes namely Deep, Moderate, Early, Normal and ONH.The single scale CNN consists of single flow of network. The advantage of multi-scale over single scale network is that it improves the performance results. The input image is divided into several blocks and each block can be different size. The performance improvement is proved in the next section.

IV. Experimental Results

The proposed method is tested on RIM-ONE release 1 (r1) [25] dataset, which consists of 455 images. The images in the dataset consist of 255 normal images and 200 glaucoma images. In this work, this classification is further divided into five classes. The details of grade classification of RIMONE – r1 dataset is shown in Table 2.

Table 2 Grade Classification in RIMONE – r1 Dataset

Class	Grade	Number of Images
Glaucoma	Deep	70
	Early	60
	Moderate	70
Normal	Normal	200
	ONH	55

Table 3 gives the hyperparameters that are used to train and test the network. The proposed model is evaluated using accuracy, specificity, sensitivity, precision and F1- score.

These are calculated using True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The formulas for these metrics are displayed in Table 4.

Table 3 Hyperparameters Settings

Parameter	Values
Optimizer	Sgdm
Learning Rate	0.0001
Mini Batch Size	8
Max Epochs	10

Table 4 Performance Metrics

Measure	Formula
Accuracy	$Ac_r = \frac{TP+TN}{TP+TN+FP+FN} \times 100$
Sensitivity	$Sensitivity = \frac{TP}{TP+FN}$
Specificity	$\text{Specificity} = \frac{\text{TN}}{(\text{FP}+\text{TN})}$
F1 - score	$F_m = 2 * \frac{Precision * Recall}{Precision + Recall}$
Precision	$Precision = \frac{TP}{TP+FP}$

The results obtained by the proposed model are displayed in Table 5. We compared the results of the proposed method with single scale CNN such as VGG and GoogleNet. It is also compared with TT_CNN method which we have proposed previously. The proposed method is also tested with RF classifier. All the results are compared in Table 6.

Table 5 Results Obtained by the Proposed Method

	Accuracy	Sensitivity	Specificity	Precision	F1 score
VGG	0.96	0.89	0.97	0.90	0.90
GoogleNet	0.96	0.90	0.98	0.90	0.90
MTPRCNN	0.97	0.91	0.98	0.91	0.91
TT_CNN + RF	0.97	0.92	0.98	0.92	0.92
Proposed CNN + RF	0.98	0.93	0.98	0.93	0.93

From Table 5, it is observed that the accuracy of the proposed method is 0.01 higher than VGG and GoogleNet models. When the proposed model is combined with RF classifier, there is a 0.02 increase in accuracy and 0.03 increase in sensitivity. Figures 5 and 6 display the bar chart showing the accuracy and sensitivity comparison of the compared models.

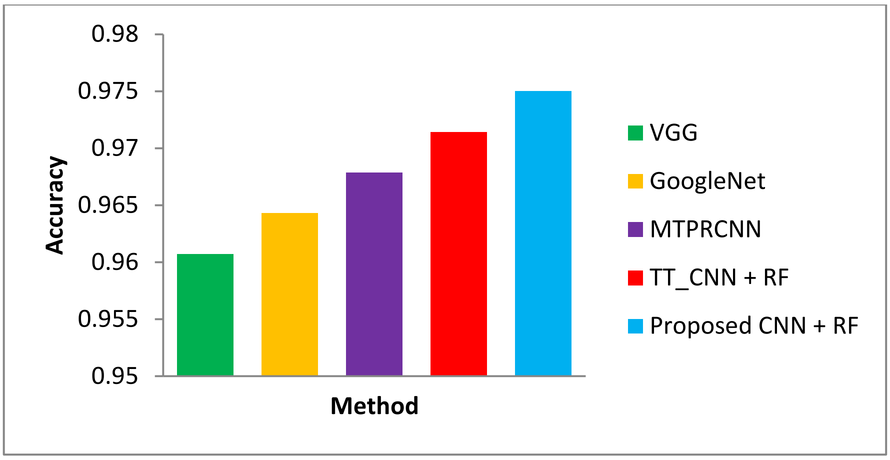

Fig. 5 Accuracy Comparison of Proposed Method with other Methods

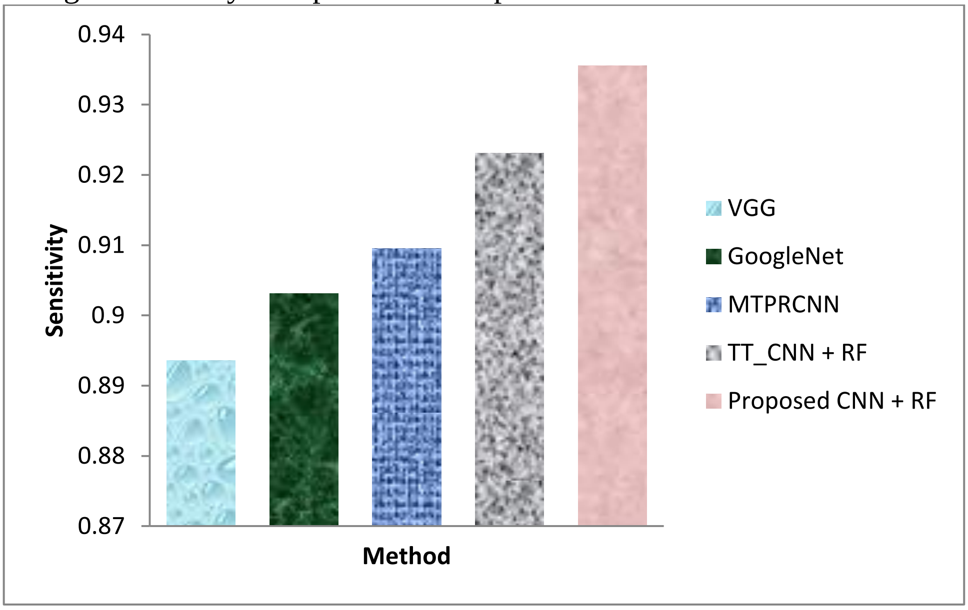

Fig.6 Sensitivity Comparison of Proposed Method with Other Methods

V. Conclusion

Glaucoma is one of the major disease found in retina. There are several automated methods for glaucoma detection. In this paper, we propose a MTPRCNN with three tiers for glaucoma detection. The retinal images are decomposed using EWT which is then given to the designed CNN. For this experiment, the RIM-one r1 dataset is divided into five different grades. Experiments are conducted in two different ways: the designed MTPRCNN is used as feature extractor and classifier, designed CNN as feature extractor and RF as classifier. Both the results are compared with the popular VGG and GoogleNet. The proposed model outperforms other models with little increment in accuracy.

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